Visualization Badges: Communicating Design and Provenance through Graphical Labels Alongside Visualizations

Valentin Edelsbrunner, Jinrui Wang, Alexis Pister, Tomas Vancisin, Sian Phillips, Min Chen, Benjamin Bach

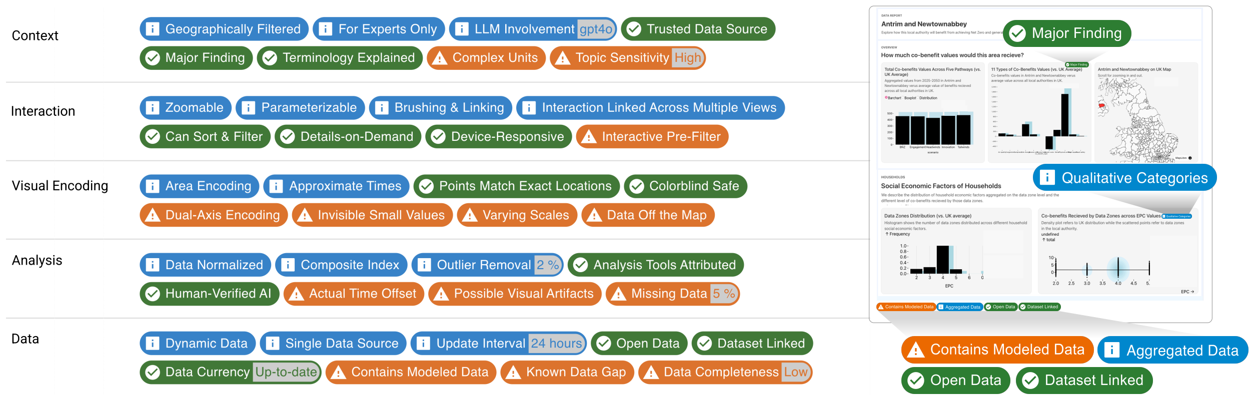

Fig. 1: Examples of visualization badges, ordered by scope and colored by intent (left). Real-world use of visualization badges, illustrating how authors use badges to communicate provenance and design decisions to readers (right).

Abstract—This paper presents Visualization Badges, graphical labels shown alongside visualizations to communicate provenance and design considerations to enhance understandability and transparency. Badges may, for example, highlight a major finding, disclose that an axis has been truncated, or warn of possible visual artifacts. Inspired by nutrition and energy labels on product packaging, visualization badges aim (i) to allow visualization authors to justify and disclose analysis and design decisions and (ii) to make readers aware of important information when viewing and interpreting visualizations. Collectively, visualization badges aim to foster trust in visualizations and prevent readers from drawing incorrect conclusions. Based on a series of co-design workshops, we define and evaluate the concept of visualization badges and formulate a conceptual framework for analysis, application, and further research. Our framework includes a catalog of 132 visualization badges, categorization schemes, design options for their visual representations, applied visualization examples, and guidelines for their use. We hope that visualization badges will help communicate data and collectively improve communication, visualization literacy, and the quality of visualization techniques. Our badges, workshops, and guidelines can be found online `https://vis-badges.github.io`.

Index Terms—Data Visualization, Communication, Transparency

1 Introduction

Visualization design is the process of finding appropriate trade-offs between holistically and objectively showing data [75] and clearly representing respective patterns in the data [16]. To help visualization authors arrive at informed decisions, several guidelines and conceptual frameworks [26, 27] have been created, ranging from theoretical approaches as well as evidence-based analyses about visual clutter and data-ink-ratio [86], memorability [8], aesthetics [55], visual artifacts [3], visualizing uncertainty [69, 71] and visual embellishments [5] to cataloging design patterns (e.g., [1]), deceptive visualization designs [70] and techniques of (unintentionally) misframing visualizations [52, 59], summarized in higher-level guidelines (e.g., [65]).

- *Valentin Edelsbrunner is with Inria Bordeaux. Email: valentin.edelsbrunner@inria.fr*
- *Jinrui Wang, Alexis Pister, Tomas Vancisin, and Sian Phillips are with The University of Edinburgh. Email: jinrui.wang, apister, tomas.vancisin, sian.phillips@ed.ac.uk*
- *Min Chen is with the University of Oxford. Email: min.chen@oerc.ox.ac.uk*
- *Benjamin Bach is with Inria Bordeaux, and the University of Edinburgh. Email: benjamin.bach@inria.fr*

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However, even if we assume that most visualization authors aim to create efficient and truthful visualizations, no visualization will probably ever be free of defaults, and readers will always find some reason for critique [48]. Furthermore, it is well known [40, 80] that any visualization often reflects decisions made 'further up' in data collection and analysis. For our work, we assume *no bad intentions* on the side of a visualization author—a designer, analyst, domain expert, journalist or team thereof—but nonetheless wish to pose the following question: *How can visualization authors alert their audience of potential pitfalls and also furnish important provenance information [66] to their users?*

This constellation is particularly evident in the context of an increasing number of visualizations in the public realm. Some of these visualizations are embedded in extensive analyses of large data, such as dashboards, news articles [44], or visualization atlases [91]. Other usages are optimized for communication [76], such as data GIFs [78] or data videos [77]. Again, others target audiences potentially unfamiliar with many concepts in visualization, statistics, and data literacy, such as data comics [4]. In many of these examples, a reader has limited capacities (time, ability, knowledge) to scrutinize a visualization design and the underlying analysis through footnotes or sophisticated interactive tools (e.g., [18]). A lack of scrutiny can lead to misreading [48] and mistrusting visualizations [22]. On the other hand, communication requires making complex data as simple as possible [75].

In this paper, we present the concept of Visualization Badges (Fig. 1), a set of *concise graphical labels shown alongside a visualization to disclose information about visualization design and data provenance*.

Inspired by well-known labels for food nutrition, energy consumption for consumer products, or quality badges in code repositories, visualization badges provide an *author-defined* 'scent', that is an additional furnishing of a visualization with information by an author to foster readers engagement and interpretation. For example, a badge can alert a reader to potentially missing or uncertain data Known Data Gap, the use of non-standard scaling Adjusted Baseline, or that the visualization may lead to misinterpretation due to perceptual issues Possible Visual Artifacts. Likewise, badges can confirm that data is available for download Open Data, or that a linear scale is used Standard Scale Used. By disclosing information in a light, yet visually salient way, badges aim to prevent readers from missing information provided in text or hidden behind interactive features and can offer further information on demand, for example by hovering over or clicking on individual badges. As a long-term objective, with more badge-mediated communications among visualization authors and users, visualization badges aim to foster trust in the visualization and improve visualization literacy collectively. In developing a conceptual framework for creating visualization badges and fostering their application, this paper makes several contributions:

- *(i)* a catalog of 132 *binary* badges coded from scientific papers, news articles, and co-design workshops (Sec. 3);
- *(ii)* a description of schematic information for badges, including badge intent (*positive, negative, neutral*), scope (*data, analysis, visual encoding, interaction, context*), topics (e.g., *AI, uncertainty*), as well as more complex yet expressive badge genres (ordinal, categorical, quantitative, lists, and score badges) (Sec. 4);
- *(iii)* design solutions for visually styling and integrating badges with visualizations, inspired by design observations from visual badges used to label food and other products as well as information in computing systems (Sec. 5);
- *(iv)* findings from five co-design workshops across three interdisciplinary visualization projects applying badges (Sec. 6); and
- *(v)* a set of step-by-step guidelines to apply visualization badges to any visualization project (Sec. 7.2).

Observations from the workshops helped refine our framework and show that badges are a promising means for authors to communicate provenance about data, analysis, and design. However, applying badges and deciding which ones to use is a highly contested process that is less than straightforward. In response, we discuss how our framework can inform more rigorous studies and different application scenarios. We conclude this paper with a call to action, encouraging visualization authors to attribute badges to their visualizations, reuse badges featured on our website, and contribute novel badges that we have not identified in this work; we call researchers to study the effect of badges on the interpretation of visualizations, as well as what badge attribution reveals about people's visualization and data literacy. Our badge catalog, designs, example visualizations, and guidelines are also found on our supplementary website `https://vis-badges.github.io`.

2 Background

2.1 Provenance, Uncertainty, and Trust in Visualization

A significant amount of research in data visualization, visual analytics, and data science is devoted to provenance (e.g., [37, 41]), broadly defined as the attempt to understand, capture, record, store, and communicate the transformations, decisions, and insights derived from complex workflows [73]. The information captured by provenance [73] ranges from low-level information, such as lineages or pedigrees of digital information (e.g., data origin, aggregation, formatting) [12, 79], to high-level information recording analytical insights (e.g., the history of hypotheses and findings [41] or the rationale behind decisions). Provenance serves to recall, reproduce, and verify previous analyses, recover past actions, and facilitate collaborative communication among analysts doing similar work or presenting results to the public [73].

One particular concern with provenance lies in capturing uncertainty in the data, as related to inherent randomness (aleatoric) or lack of knowledge (epistemic) [7]. Hullman [47] notes that many designers choose not to visualize uncertainty, due to concerns about reader comprehension, lack of appropriate visualization techniques, or a desire to project confidence rather than highlight potential limitations.

Trust in visualization and analysis is critical, however, as it directly shapes how people interpret information and make decisions [62]; e.g., by omitting contextual details alongside a visualization can undermine understanding and transparency [13]. While many studies suggest that disclosing more provenance information can foster trust [28, 68], too much information can have an adverse effect, shown to overwhelm readers and inadvertently diminish trust [51]. Finally, trust is inherently difficult to measure, because no consensus on its precise definition exists [62]. However, recent scholarship has begun to quantify how re-contextualizing visualizations with metadata affects trust and transparency [13, 14], indicating that while participants perceived visualizations with textual metadata as more thorough, their perceptions of relevance, accuracy, clarity and completeness remained similar.

2.2 Visualization Literacy and Design Guidelines

The ability to read and interpret visualizations correctly is called data visualization literacy [10]. Visualization literacy is often associated with deception and readers' *un*familiarity with visualizations [56]. However, as visualization design often makes trade-offs, every visualization and data analysis should be scrutinized, not because of the fault of the author or the assumed inadequacy of the reader but because of the complexity of visualization design and data analysis. Moreover, there is much debate about the 'right' visualization design; visualization authors rely on flexible principles and guidelines that often include exceptions and caveats [17]. The literature links two things: reader-centered literacy research and author-centered design guidance. For example, people discuss whether omitting a zero-baseline axis is misleading [23, 59, 70], if 3D effects obscure data [17, 59, 84], the pitfalls of using rainbow color maps [9, 74], or the risks of cherry picking data [58]. In response, researchers have cataloged many real-world examples of deceptive design [54, 59, 60] and developed rule-based guidelines aimed at preventing common pitfalls [21, 61, 67, 86, 89]. Visualization linting systems aim to help authors create effective designs by automatically finding and flagging visualization design errors, e.g., a missing legend, during the visualization creation process [19, 34, 46, 63]. In contrast to automatic linting, visualization badges offer designers a pragmatic tool for disclosing potential pitfalls in their visualizations, helping them avoid accusations of deliberately misguiding their readers. Concomitantly, visualization badges have the advantage of encouraging authors to make bold design decisions that are in the best interest of the data and the readers, instead of fearing heaps of guidelines.

2.3 Communicating Provenance and Design Decisions

We now review *how* provenance and design information can be effectively communicated to the reader. Expert systems for exploring provenance (e.g., [18, 30]) include comprehensive interactive and computational mechanisms. However, broad and diverse audiences in public settings require more concise and effective communication methods. Current strategies for communicating provenance and design rationales include footnotes and textual annotations [57, 82, 90]; design exposition through explanatory narratives alongside visualization code [95]; contextual in situ help [20]; or dedicated explanations in the form of data comics [92], cheat sheets [93] or interactive documents [29]. While being potentially very effective in understanding provenance and scrutinizing data, these approaches demand readers' time and effort.

The adoption of visual and text labels to disclose information is in fact a long-standing practice across a range of non-digital industries for example, energy labels on home appliances [11, 32]; nutrition labels on food packaging [45, 50, 94]; and more broadly, road signage systems [25], many of which formed industrial and national standards for mandatory and voluntary regulations [24, 33, 36]. Closest to our research, labels have been used to report on the technical reproducibility of figures in scientific reports [35] as well as research in computer science by the ACM.[1]

[1] `https://www.acm.org/publications/policies/artifact-review-badging`

Multiple studies have empirically assessed the effectiveness of different label design features, showing that abbreviated labels are more effective than a full nutrition description table [94]; that label placement directs attention [32]; or that pictogram visuals help overcome language barriers [88]. However, other studies show inconclusive results with respect to public support [43], decision-making [43], and attention capture [15, 38]. In this paper, we aim to first and foremost provide a system for creating visualization badges that can later inform bespoke, yet more complicated, user studies.

3 Badge creation and analysis

To explore the idea of visualization badges, we created a comprehensive list of badges, their possible attributes, and a taxonomy of these badges. To that end, we collected information considered relevant for display alongside visualizations, employing three complementary approaches. Each of these collection methods yielded a set of badges that were consolidated, refined, and analyzed into a comprehensive list of 132 badges. Full details of our methodology and manual coding can be found in the supplementary material (Appendix A).

3.1 Badge Collection

First, we conducted a scoping review of 33 **scientific papers** presenting frameworks, studies, and guidelines on data provenance (e.g., [39, 72]) design flaws (e.g., [54, 59]), best practices for designing visualizations (e.g., [48, 64]); and metadata, trust, and visualization design communication (e.g., [13, 14, 31]) mainly from the following venues: *ACM CHI*, *Communications of the ACM*, *EuroVis*, and *IEEE VIS*, *PacificVis*, *TVCG*, many of which are cited in the related work already (Sec. 2).

Second, we manually coded 80 **news articles** from well-known news magazines (*Financial Times*, *The New York Times*, *The Economist*, *The Guardian*, *The Times*, *BBC News*) with 3-5 individual visualizations per article (313 in total). All of these articles were previously used in [44]. For each visualization, we recorded (i) information disclosed in the figure caption, and (ii) information the authors of this article would have added had we been the visualization authors.

Third, we conducted three **co-design workshops with domain experts** with the aim of creating and designing visualization badges for their respective projects. Each of the three workshops was conducted with a different team of collaborators with whom we currently work and design visualizations for. The first project, Peace Visualization [6], is concerned with visualizing data from peace agreement text documents to track peace processes and inform policy makers and peace builders. The project heavily relies on automatic natural language processing and human qualitative coding; their visualizations often display highly uncertain as well as complex information patterns often about politically sensitive topics. The second project is geared toward development of a visualization atlas [91] to inform policy makers, scientists, and the general public on co-benefits of CO_2 emission reductions [83]. The extensive dataset is created by a supercomputer model calculating benefits up until 2050 across multiple possible futures. The last project is led by NASA [53] and concerns a hyperwall public dashboard displaying dynamic live data about Earth's vital signs, shown through sophisticated high-resolution scientific visualizations for public audiences. All three workshops comprised 15 scientists representing their respective domains and the authors of this paper as visualization designers.

3.2 Badge Consolidation and Analysis

Our first step involved badge consolidation. To achieve this aim, we decided to exclude badges about purely deceptive design flaws that would not be assigned by the author themselves. For example, badges warning a reader about "illegible text" or "missing legend", is not directly relevant to authors aiming to disclose information for improved visualization interpretation. In our list, these badges almost exclusively originated from the context of linting and design flaws (e.g., [54, 63]). We also removed and aligned duplicates, made badges atomic by creating short label descriptions, and created an iterative coding scheme including badge intents, genres, scopes, and topics, all detailed in Sec. 4. The final catalog of badges is found on our supplementary website `https://vis-badges.github.io` and in Appendix C.

4 Visualization Badges

In this section, we present a structured analysis from the badge collection and consolidation process, which led to definitions and a more comprehensive formalization of the concept of visualization badges. A badge's **label** is a concise textual name (ideally 2–3 words) that succinctly conveys the information or decision disclosed by the badge. Example labels include AI-Derived Insight, Aggregated Data, or Correlation $\neq$ Causation; labels should be as specific as possible. The badge **description** is a more detailed textual explanation that provides context or clarification to help interpret the badge label. The following is an example description for Truncated Axis: "The axis starts from a non-zero point because most data points fall in this narrow range". A description can be shown, for example, via a mouseover (Sec. 5), and it can also help an author understand the purpose of assigning a particular badge during the design process. Finally, a badge also comprises the following set of attributes: an *intent*, a *genre*, a *scope*, and one or more *topics*.

4.1 Badge Intent

The **intent** of a visualization badge specifies the interpretative stance (or purpose) of the badge. During our coding and co-design processes (Sec. 3), we found that the collected badges naturally aligned on three core interpretative stances (positive, neutral, warning), leading us to settle on three instances for badge intent:

- **Positive (confirmation) badges** refer to information that supports the correctness of data collection, analysis, or visualization design; they also provide information in the service of verification and scrutiny (e.g., data availability, source attribution). Confirmation Badges aim to foster trust and confidence in the information displayed in the relevant data visualization. Examples of positive badges include Open Data, Colorblind Safe, or Data Up-to-Date. Descriptions for confirmation badges will most likely include additional information, such as links to the open data used, scope for colorblindness tests, or information about the currency of the data.
- **Negative (warning) badges** highlight aspects of the data, analysis, or visualization that warrant caution or critical attention in the instance of visualization interpretation. Such badges serve to alert readers that extracting insights might not be as straightforward as it first appears. While these badges can be aimed at less experienced audiences (particularly for complex visualizations), they also benefit expert analysts by drawing attention to underlying assumptions. Examples of warning badges include Inverted Axis, Known Data Gap, Small Values Exaggerated. Unlike confirmation badges, warning badges require at times very detailed descriptions, e.g., explaining the specific fallacy as well as providing any justification for why this fault is present in the visualization, for example, the reason for the axis inversion, specification of the gap period, or threshold at which the data is exaggerated.
- **Neutral (information) badges** convey information that either *(a)* has no intrinsic positive or negative implications, or *(b)* involves both potentially beneficial and harmful effects. Examples include Approximate Times, Dynamic Data, or Area Encoding.

For the vast majority of our badges, we were able to assign a clear intent (positive, negative, or neutral). However, for certain badges, the intent strongly depends on context and, thus, must be determined by the visualization author. For instance, Outliers Removed might signal caution in excluding potentially important data points, but can also indicate the author's concerted attempt at presenting a correct picture by preventing extreme values from skewing the analytical result.

4.2 Badge Genres

Next, we identified six badge genres, each implying a slightly different way of structuring or presenting the underlying information. The motivation for these genres came from observations during our coding process, such as the fact that some visualization badges were mutually exclusive Single Data Source vs. Multiple Data Sources; some naturally formed groups *Target Audience*={For Policy Makers For General Audiences, For Experts Only}; or some included nuances like Prediction Confidence=*high*, *medium*, or *low*. Although badge genres are orthogonal to badge intents, they add further structure and semantics to visualization badges and can influence their visual design.

- **Mono badges** or **binary badges** are the simplest form of a visualization badge, consisting of only a badge label, such as Colorblind Safe. This badge genre has no attribute and is only applied if the respective information is intended to be disclosed or not. The absence of a specific mono badge does not imply the opposite to be true, but rather, may indicate that the author did not consider the badge relevant for their audience or simply did not think of it.
- **Ordinal badges** can appear to different degrees, for example *yes/no* or *full/partial/none* or any other ordered set of values. Each attribute can change the badge's overall intent. For instance, an ordinal badge Data Source Currency (Up-to-Date, Slightly Outdated, Outdated) sets a clear, ordered scale. Unlike mono badges, ordinal badges imply consistent use across visualizations by explicitly stating the (in)existence or degree of a feature. The genre of badges is comparable to nutrition or energy labels on consumer goods.
- **Categorical badges**, unlike ordinal badges, can have multiple states or attributes *without* implying any order or changing intent. For instance, a badge Visualization: Public Domain/Creative Commons might indicate different licensing types. Such badges let authors specify relevant categories, rather than a progression or scale.
- **List badges** can be best thought of as semantic badge groups. While categorical visualization badges show a single attribute, list visualization badges can contain multiple, valid values. For example, Interaction [Hover, Brush, Zoom] displays available interactions.
- **Numerical badges** display a single attribute as a numeric value or quantity, for example Update Frequency: 7 days or Missing Data: 5%. A visualization author can adjust this value for each visualization as needed
- **Score badges** are a hybrid of numerical, ordinal, and list badges. They reflect how many predefined attributes (out of a specified total) apply, for example 3/7 (three out of seven). While potentially rare, one workshop group created a score badge, Open Data Practices (n/5) as the combination badge of Open Data, Data Source Disclosed, Dataset Linked, Raw Data Available, and Data Up-to-date. For each visualization, the badge would then specify which predefined attributes apply and how many are relevant.

As previously stated, a visualization badge can adopt different genres depending on the needs of a visualization project. For instance, the choice to truncate an axis could be expressed as *(i)* a mono badge Truncated Axis, *(ii)* an ordinal badge Axis Truncated: yes/no, *(iii)* part of a list badge Visual Deceptions: truncated axis, inverted axes, overlapping items, or *(iv)* a score badge Visual Deceptions specifying *truncated axis (yes/no)*, *inverted axes (yes/no)*, and *overlapping elements (yes/no)*.

4.3 Badge Scopes

In addition to intents and genres, we identified a set of *scopes* to group the badges roughly by different stages of the visualization creation process from data collection to interactive exploration. The scopes are a way to express which part of the process a badge refers to.

- **Data badges** refer to the availability of the data source, such as Open Data, and any relevant provenance information, such as the collection method API-based Collection, the type of data used in the visualization Human Survey Data, or warnings indicating potential problems Data Quality Constraints, etc.
- **Analysis badges** refer to any methodological information about how the data was cleaned, processed, and analyzed, such as Null Values Removed, Rounding Errors, Data Normalized, etc.
- **Visual encoding badges** refer to any information related to visualization design and mapping leading to improvement of a user's reading experience or fostering interpretation. These badges are dedicated to highlighting deliberate design choices and their rationale, as disclosed by the author, in addition to serving as warnings, information, or confirmations. For instance, Rainbow Required and Dual Axis Encoding often serve as warnings, while Printer Friendly and Colorblind Friendly function more as confirmations. They can also disclaim unintentional visual artifacts or special patterns that result from data input, such as Invisible Small Values.
- **Interaction badges** refer to the interaction of a visualization. They can point to the availability of interaction on a general or specific level, such as Zoom-able and Can Mouse Over. They also point to the application of an interaction *by default*, such as Interactive Pre-Filter, where certain data elements were preselected, but can be unselected and tweaked by users for deeper exploration.
- **Context badges** refer to the background and situational information necessary to understand the visualization, including the intended audience, citations, attributions, and other contextual information, often referred to as metadata, such as Expert Involved or Major Finding.

4.4 Badge Topics

Despite the addition of exclusive badge scopes, we identified many groups of badges that were difficult to describe in a strictly taxonomic way. Consequently, we refined a set of free-form tags that resulted in 23 low-level badge topics, such as *attribution* (7), *uncertainty* (16), *bias* (8), *NLP* (5), *time* (6), *transformation* (6), etc. Badge topics complement the existing dimensions, offering a flexible layer to organize and structure potentially many badges. For example, there are five badges assigned to the topic *maps* under the scope of visual encoding, such as Non-Area-Preserving Projection. Topics are also more flexible as they allow for overlaps and coexisting classifications. One badge can belong to multiple topics, and one topic can include badges from multiple scopes. Since our example badges in the list are highly contextual and not exhaustive, the topics presented are not meant to be definitive. Instead, this category creates a flexible framework for visualization authors to search, shape and surface topics.

5 Visualization Badge Design

In this section, we describe a design approach to address *how* to present the badges' dense information concisely, and how visualization authors can integrate a badge effectively into their visualizations. Both the required badge information and its visual design can vary widely from one visualization *project* to another. The notion of visualization project refers to one or more visualizations integrated into the same medium—either explanatory, exploratory, or both—e.g., a (news) website, a dashboard, a visualization atlas, a data story, an interactive analysis tool, etc. The authors of each project may choose to create a consistent set of badges and badge designs for reuse across visualizations. In view of the fact, that the design space for badges can be very large—covering choices of colors, pictograms, shapes, font sizes, outlines, and more—we focus on describing *one* generic solution and its variations to convey badge information and represent badge attributes. Our design is informed by challenges encountered while designing badges for our collaborative visualization projects; discussions during co-design workshops; and an observational study of general badge designs in real-world applications.

5.1 Design Challenges

The following challenges were identified during our initial co-design workshops (Appendix A.1) and through our own experience designing visualizations in these projects.

C1 Visual Expressiveness. Badges should clearly communicate their genre, intent, scope, label, description, etc. Not all information needs to be shown in all cases, with some information (genre/scope/intent) possibly better suited, depending on a given project. Showing specific information about badge genres——such as all the options available for an ordinal badge——requires additional design trade-offs.

C2 Unobtrusiveness. Balancing visual expressiveness (C1) with the visual design and complexity of a visualization and its context, such as descriptive text, other visualizations, or user interface elements, can pose a challenge. Badges must not draw (too) much attention away from the visualization; they should not add clutter or obstruct content.

C3 Scalability. A question regarding how to enable the display of potentially many badges, necessary to comprehensively describe a visualization. For example, a dashboard may feature a wide range of badges including various intents, genres, and groups. However, displaying all these badges together on a single dashboard page can put pressure on C2.

5.2 Design Inspiration from Real-World Examples

When badges are used in public contexts and applications, this can be regarded as evidence that their design has “stood the test of time”. A preponderant number of badges is documented in scientific papers or policy reports (Sec. 2.3). For our research, we collected visual badges and labels from food and product packaging, web applications (e.g., GitHub [96]), and dashboards (e.g., [1, 85]). Across all these examples, often referred to as "labels" in their original contexts, we identified the following *design elements* and their usage (Fig. 2).

- **Colors** commonly used to indicate the interpretative stance. Green is frequently used to signal positive meanings, such as healthy food, stable code builds (GitHub), or shortest paths (Google maps). Blue, white, and grey serve for neutral information. Yellow and orange suggest caution, warnings, or medium severity issues. Red was reserved for the most critical issues.
- **Pictograms and Shapes.** Visual cues about badge meaning and intent are often provided through pictograms and badge shapes. Common examples include exclamation marks or warning triangles to signal an alert (e.g. service disruption warnings in Fig. 2(d)), checkmarks to indicate that something has been verified or completed, and pictograms representing context-specific attributes (e.g., a *flag* inside a red diamond + label *Ethnic disparity likely* in Fig. 2(f)).
- **Text and Labeling.** Labels are typically concise, often consisting of 2-3 words, for example, *Planned service changes* in Fig. 2(d). Though already concise enough, the labels are also space efficient because they are often only visible when interacting with the pictogram or listed under a chart (Fig. 2(f)).
- **Attributes.** Badges frequently encode ordinal values (e.g., *A-F* grading on the European energy pass), quantitative values (e.g., dish under 500 kcal on restaurant menus, PET1 on plastic types), states (e.g., in progress, certified by). Usually labels are encoded with colors in addition to the values being explicitly stated e.g., nutrition labels in Fig. 2(a) have their classifications colored and labeled.
- **Placement and Aggregation.** Multiple badges are often grouped together such as on top of a GitHub Readme file (Fig. 2(e)), or positioned in close proximity to the content/context they elucidate, such as the traffic condition warnings specific to certain steps in the turn-by-turn navigation.
- **Double Encoding.** Specific combinations of shapes and colors are used to reinforce meaning (e.g., orange warning triangle, green checkmark and blue information icon).

5.3 Design Space

Our badge design includes three dimensions: the *visual design* (Fig. 3); *placement* and *aggregation* (Fig. 4); and finally *interaction* (Fig. 5). As part of a conceptual framework for visualization badges, our designs aim to highlight important options and decisions available to designers. In any given visualization project, the badge designer may modify and adapt these designs to integrate badges with the visualizations and other project elements, to ensure a balance between expressiveness, unobtrusiveness, and scalability.

Visual design. A badge can be devised from up to four visual elements: (a) its *textual label*; (b) a *pictogram* encoding either its genre, scope, or topic; (c) a *backdrop* that can be (i) colored according to the badge's genre, scope, or topic, or (ii) kept in either a consistent color or shown as outline so as not to distract from the visualization (C2) (Fig. 3(d) Variations); and (d) a *qualifier* showing badge attributes specific to each genre (explained further below).

In our designs and across our collaborative projects, we chose pictograms and colors to represent intent as follows: orange and a triangle-shaped warning sign for warning badges, inspired by the use of triangles

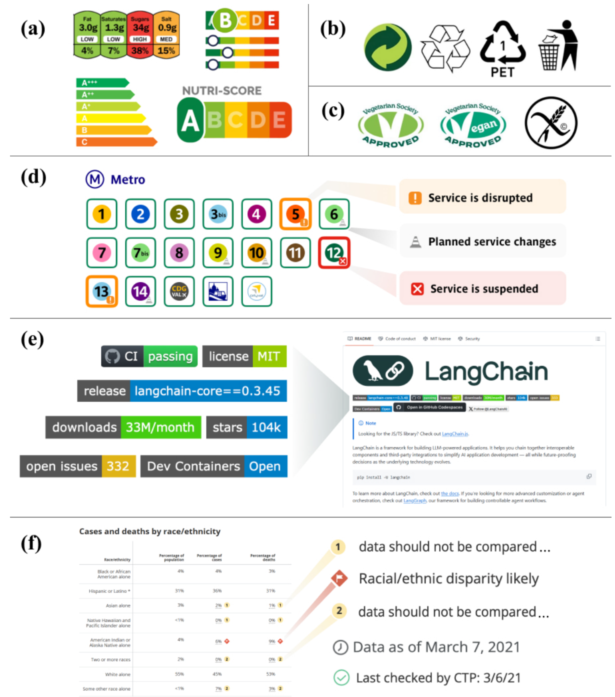

Fig. 2: Badges in the context of a) consumer products b) recycling, c) food certificates, d) commuting, e) computer science and f) COVID tracking dashboards.

in road signs, map applications, and dashboards; green and a circular check mark for confirmation badges, inspired by similar use in internet applications; and blue and a square pictogram with a lowercase ‘i’ for ‘information’ inspired by icons in public spaces (Fig. 3(a)).

Badge modes. Combining these visual elements, we created designs for display modes that differ in size and vary the amount of information shown (Fig. 3(c)):

- In **MINI** mode (Fig. 3(b)), a badge consists only of a circular backdrop with a pictogram specifying the genre or scope, as chosen by the badge author. Mini badges take minimal space and can, if needed, be placed directly in the visualization near any element to which the badge explicitly refers (see Fig. 4). There is no visual difference between the badge genres in MINI mode because MINI badges do not display any genre-specific qualifiers.
- In **LABEL** mode, a badge shows its label alongside an optional icon on its backdrop and includes a minimized qualifier. Each badge genre has a slightly different qualifier design depending on its attribute(s), except for mono badges, which have no qualifiers (as they have no attributes). Ordinal and categorical badges are visually split into two parts: one part features the badge label, and the other part shows the selected attribute. List badges show a small offset number that indicates how many elements are in the list (but not their names). Quantitative and score badges show the number or score in the same way as ordinal badges but do not list the elements scored.
- In **FULL** mode, a badge shows any of the detailed attributes for ordinal, categorical, list, and score badges. This includes all the options an ordinal badge can have (inspired by the ABCDE nutrition label, Fig. 2(c)-left); or all the elements in a list badge; or all the elements that make up the score (inspired by the energy score label (Fig. 2(c)-right) and a more extended version of the ABCDE nutrition label design, Fig. 2(c)-center). Mono and quantitative badges do not display beyond what is shown in LABEL mode. Additionally, we explored more nuanced visual variations for LABEL and FULL badges in Fig. 3(d) using different shades, outline styles, button shapes, and other alternatives in displaying the attributes.

Badge placement. We identified three options for badge placement in relation to one or more visualizations (Fig. 4):

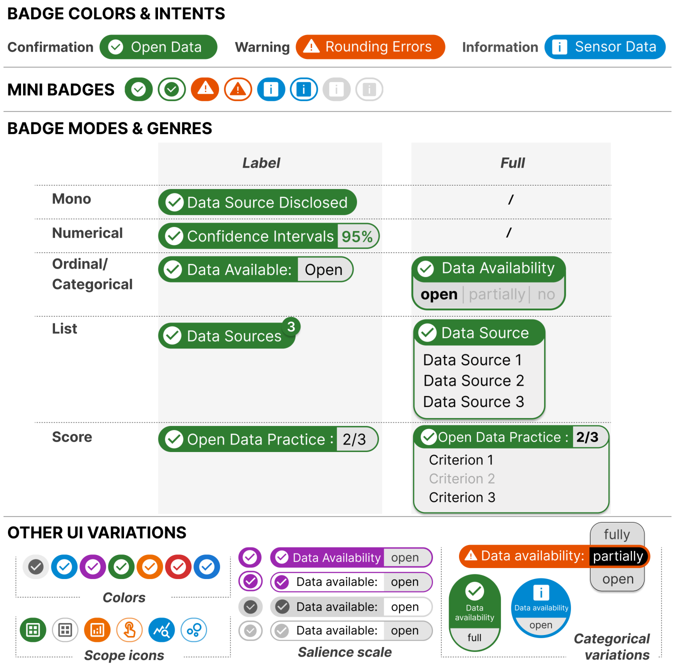

Fig. 3: Badge visual design options: a) color usage in assigning intents: green-confirmation, orange-warning, and blue-information; b) MINI mode badges in different colors; c) badge genres representation in LABEL mode and FULL mode; d) UI variations in shades, shape, and attribution.

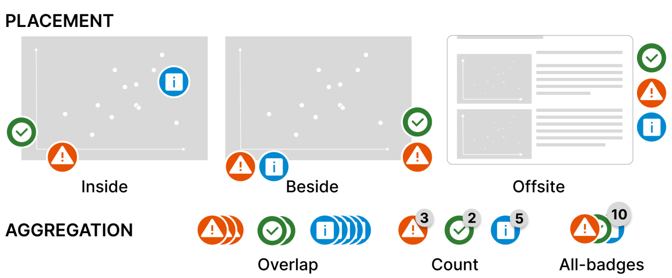

Fig. 4: Badge placement options Inside, Beside, and Offsite and badge aggregation options Overlap, Count, and All-badges.

- *Inside* a visualization, where a badge can refer to individual visual elements and disclose information about them. This is similar to linting approaches [19] or small warning signs placed within a table or dashboard (Fig. 2(f)). However, placing badges inside may occlude content (C2), and many of our badges do not refer to individual elements but are applicable to the entire page.
- *Beside* a visualization to indicate that the badge refers to the entire visualization. Badges can be shown vertically on either side of the visualization, or horizontally above or below the visualization
- *Offsite* placement refers to badges placed not directly alongside a visualization but badges referring to multiple visualizations, for example, an entire dashboard, a news page, or a set of small multiples.

In any of these cases, badges can be ordered and grouped by any of their characteristics in Sec. 4; intent and scopes (we did not come across any case where badges would be grouped or ordered by genre)—or an author-defined priority.

Badge aggregation. To avoid clutter (C3) when applying many badges to a visualization (inside, beside, or beyond), a simple way is to show MINI badges instead. We describe three ways to aggregate badges as demonstrated in Fig. 4(a); (i) *overlapping* badges grouped by intent (or scope or topic); (ii) aggregating badges based on a criterion (e.g., intent) and adding a small number indicating their overlapping *count*, or (iii) aggregating *all-badges* while showing the intent icons that are in the badge set. Each of these designs presents a further trade-off between the amount of information shown (e.g., by overlapping

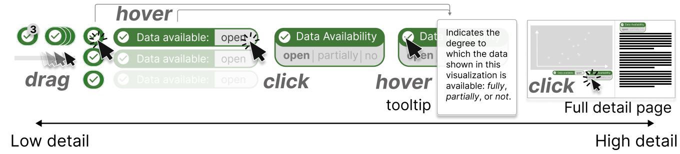

Fig. 5: Interaction used to gradually reveal more detail about a badge.

individual badges) with the space and visual attention attracted. While Fig. 4 shows badges grouped by *intent*, aggregation can be based on any dimension, e.g., on topics to keep data provenance separate from visual-encoding badges.

Interaction. Interactive features can allow a visualization reader to explore badges and obtain more information while offering flexibility for authors to provide minimized views. A possible set of interactions (from left to right in Fig. 5) is to *drag* onto a count aggregation of badges to gradually open it up into an overlap aggregation and eventually individual badges. Then one uses *drag* again to turn the MINI design into a LABEL and eventually FULL design. *Hovering* over a badge for any of the aggregations or designs shows a tooltip with the badge description. *Clicking* a badge can lead to more detailed descriptions.

6 EVALUATION

To evaluate our framework of badges, their attributes (Sec. 4) and designs (Sec. 5), and to discuss how badges are applied by visualization authors, we conducted a second round of co-design workshops with two of our three ongoing collaborators described in Sec. 3: Peace Visualizations and Co-benefits Atlas. The goal of these workshops was to assess whether visualization authors would find the badges useful in real-world contexts; which badges they would choose and why; and which badge genres and design options they prefer. In total, we had 12 participants across both workshops, including three co-authors of this paper. These co-authors are not quoted in this section but participated in their roles as visualization designers for the collaborative projects; for this study, they helped facilitate discussions and aimed to understand future visualization design requirements and the integration of badges in their respective projects. Each workshop lasted two hours, during which all participants assigned badges to the same visualization—either one they had created or were very familiar with. First, participants were invited to read through our badge catalog and were introduced to our design options (30min). Then, each participant individually chose badges and potentially created new ones for the shared visualization projected in the room for 30 minutes. Eventually, we discussed each participants choice and their rationales for selecting particular badges and designs (60min). After the workshops, the participants completed a short questionnaire containing six open-ended questions. The questions were designed to gather feedback regarding missing badges, design suggestions, and participants' perceived benefits or limitations of the badges. This resulted in three real-world examples for specific use cases in which visualization authors tagged their own visualizations using our vis badges catalog (Fig. 6). High-resolution versions of each example can be found on our project webpage `https://vis-badges.github.io`. Our main findings were as follows.

Use & benefits: How have badges been used in the workshop?

Wide range of badge intents used, but reluctance to use warning badges—Fig. 7 shows the distribution of badges by badge intent (rows) and badge scope (columns) across all workshops. Participants selected more confirmation badges (58%) than warning badges (23%) and neutral badges (19%). Interaction badges were liked for *"less time spent on finding out what functionality the vis has."*[P5] Overlapping Elements was another popular badge in the Peace Visualization workshop, used as a disclaimer for design decisions *"as there currently aren't any zoom features, it would be good to point out that there are overlapping data points in this visualization, just to fit the screen."*[P14]

A possible reason for the high number of data badges could have been that these badges simply were closer to our participants' expertise, i.e., the fact that they spent most of their time on the data, data collection, and analysis, rather than on visualization design. Another factor

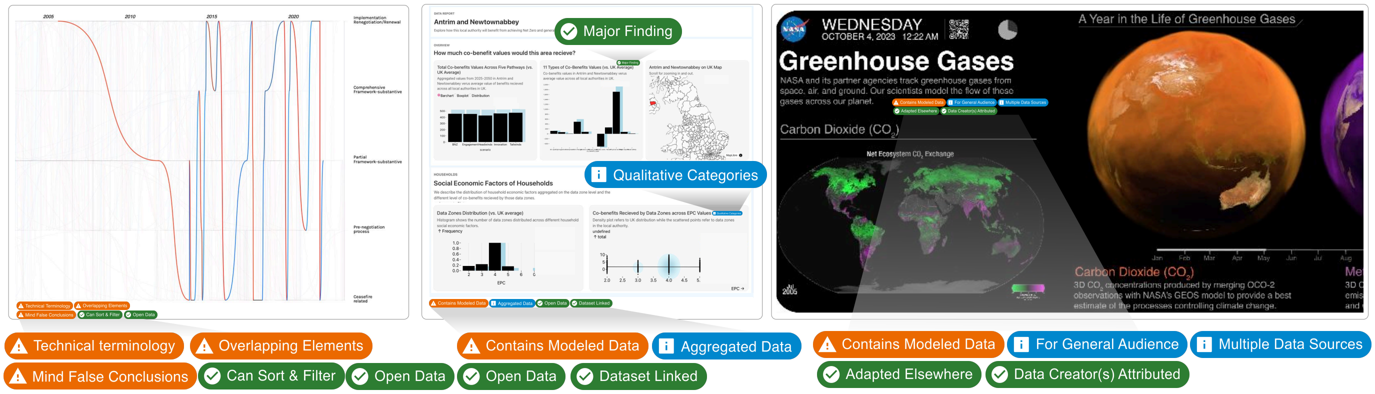

Fig. 6: Three real-world examples from our co-design workshops (a) Peace visualizations, (b) Co-Benefit Atlas, and (c) Earth dashboards. Badges were selected based on participants' feedback, prioritizing badges that came up frequently during discussion (Appendix B).

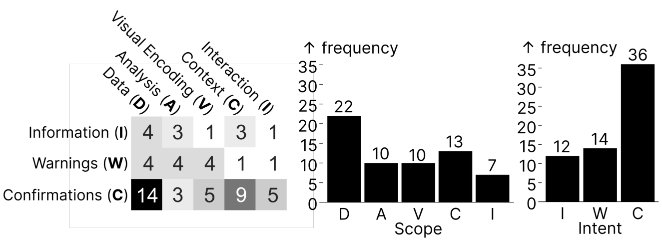

Fig. 7: Results from the evaluation workshops describing the distribution of participants' selected badge intents (rows) and scope (cols).

might be that the workshop visualizations were fairly commonly used charts that did not rely on many visual mappings were hence not overly complex. However, many participants were reluctant to use warning badges out of fear of making the analysis appear "weak": *"a lot of warning badges [is] off-putting [...] it's like anti-smoking warnings."*[P8] This hesitation reflects findings by Hullman [47] that journalists often avoid showing uncertainty because it could weaken the message they wish to convey. Furthermore, too many warning badges could also make it difficult for readers to interpret visualizations, given all the additional caveats and constraints. Both reasons, according to workshop participants, could potentially reduce trust in the visualization analysis.

Badges perceived to increase trust and show goodwill. All participants agreed that badges can help increase trust and transparency in their data and analysis. Badges *"should provide important information to help users interpret the data correctly"*[P9], can *"assist with trust building"*[P7], and *"engage with the visualizations with a critical view."*[P3] They also *"give reassurance [readers] are interpreting [the visualization] as they should, and would save time for them to figure out different levels of reliability of the data."*[P14] Across workshops, participants appreciated that badges *"simply highlight [and provide an] option to dig deeper if the audience wishes."*[P7] and can *"be used to show people what different domains/expertise is necessary to create a visualization like this"*[P14], or how to read it.

Fear of causing badge anxiety and badge inflation. Many of our participants were reluctant to use numerous badges alongside their visualizations, fearing it might cause *"badge anxiety"* and *"badge inflation"*. Both terms came up in our discussion to describe the possibly negative impacts of showing too many badges alongside a visualization. Maximizing transparency might involve a large number of badges (covering every stage of the visualization creation pipeline, considering all kinds of confirmations and warnings). Too many badges would lead to information overload, confusing people as they would need to interpret all this information and integrate it into their respective projects. Second, badge inflation is in conflict with our initial idea of visualization badges as 'communicating important information a visualization author wants their reader to take into account', turning them instead into a tool for disclosing *any* kind of information. Effectively, *"there's probably a maximum number of badges people can take into account."*[P9]

Consistency and maintenance pose further challenges, especially for large projects with many visualizations or frequent updates: *"if you badge everything and you miss [one] badge, for example, if you add 'contains predictions' [to some visualizations], the absence of this badge does not necessarily mean that the data contains reality or [that it] is not predicted. [The] same goes for 'uncertainty shown/not shown'."*[P9] When asked about a "reasonable" number of badges, participants converged on 3–5 per visualization.

Prioritization was considered essential for solving badge anxiety and inflation, i.e., the team decides which badges are more or less important and then determines how to show different priorities alongside visualizations. For example, the most important badges would be displayed beside a visualization in LABEL-mode (Sec. 5), while less important ones would appear in MINI-mode or in an aggregated form. A third group of badges might span the entire visualization project, rather than a single visualization. Examples include Contains Modeled Data or Manually Collected Data. These badges—naturally about data, analysis, and context scopes—could be shown on the front page of the visualization project, at the top of a page, or at the bottom of a page. Eventually, there could be a companion page that lists more badges relevant to the project, but less critical to show beside every visualization.

Assigning badges was considered a highly subjective task that requires prioritization, in-depth discussions, and clear decisions: *"But the question is where to draw the line? [For example,] we can assume that if [readers] look at a graph until '2050' that it contains predictions, but it depends on the audience I guess (laughing)."*[P8] Much of the above discussion was about finding trade-offs between seemingly competing goals: being transparent while not overwhelming readers; disclosing important information while knowing what is important for your audience (*"Don't state the obvious"*[P9] and *"We should only add badges [beside] a visualization when there is a very good reason to alert users, for example, [not] if data binning is standard practice for this dataset, but [if] the axis is [surprisingly] truncated."*[P7] Yet, many of these decisions felt subjective and the participants were not sure how to justify their decisions, calling for more project internal discussions and guidelines: *"[This] matters from an ethical perspective because we are placing a value judgment on what is most important for ourselves."*[P7] Other participants added that badges eventually *"rely on honesty of the developer which can be problematic."*[P5]

Visual design: Were the badge designs clear for participants?

Colors were found intuitive, pictograms were essential. Participants found our badge design rather intuitive and did not ask questions about their encoding or meaning. Participants appreciated the color highlighting for the three intents (warning-orange, confirmation-green, information-blue) and found pictograms useful for conveying that these badges disclose information about the visualization, as opposed to being 'random text' alongside a visualization. Pictograms were also perceived as affordances for interaction, such as hovering or clicking. Participants considered the chosen pictograms for information, warning, and confirmation badges to be reasonable choices.

Less salient designs were preferred. One obvious reason was to avoid badge anxiety by not making badges so prominent that they overshadow a reader's focus on the data. *"The first objective is for people to engage with the data/visualization rather than immediately telling them about all the warnings."*[P7] The second reason was the realization that badge assignment is often subjective. Hence, participants thought to solve this uncertainty (and reliability) by making badges less salient in the overall user interface. Further solutions discussed were to make badges conditional, for example, by showing a badge only when certain values are selected or a specific pattern is on display Overlapping Elements. The final option to make badges less salient was intended to allow users to turn labels on and off with an UI toggle.

Badge placement can be used as 'attention roadblocks'. While we initially considered badges as non-intrusive to the visualization, the workshops revealed instances where badges were placed *inside* a visualization and in close proximity to its content, leading us to include this option in our placement designs(Sec. 5.3): One scenario *(a)* involved badges overlaid on the visualization before any occurring interaction to alert users to data availability, domain-specific knowledge, or particular visual encodings: *"as a designer I'd want to draw people's attention to at least glance at the badges before viewing the visualizations as a 'heads-up'."*[P3] Once users interacted with the visualization, the badges would move outside the visualization. In a second case *(b)*, badges were placed directly on visual marks (Fig. 6-left).

Other Observations

The badge catalog was considered useful for familiarizing oneself with the badge concept and brainstorming new badges. Reviewing the catalog at the beginning of the workshop, participants voiced lots of agreement with the existing badges and learned about new badges they found useful for their specific project. While many badges were easy to understand, **some badge names remain hard to interpret**; in addition concepts arose that participants were not familiar with. Usually, these were more technical and domain-specific concepts such as Stemming Applied (in the context of natural language processing). **Other badges were considered too broad** in their meaning (e.g., May Contain Bias) which makes it *"hard to know which [badge] to pick as it covers all, but quite repetitive to include all."*[P7] Again, **other badges appeared highly contextual**. As already found when coding badges (Sec. 3), some badges would (have to) change meaning with their context. For example, it was noted that *"Outliers Removed, could be green [(confirmation)], could be blue [(information)], could be orange [(warning)]."*[P7] The workshops did not provide any final answers to such decisions but again pointed toward more project internal discussions to resolve them. The question remaining is whether such a judgment is possible on a project level or whether it has to happen on an individual visualization-by-visualization level. The workshops also **yielded further badges** for our catalog such as Composite Index, Data Off the Map or User-Tested Vis. A Major Finding badge would be assigned to a visualization to draw users' attention to its accompanying text or report (Fig. 6-center).

7 Discussion & Future Work

This research sets out to explore the idea of visualization badges; it defines the concept and creates a conceptual framework for their application, including examples, designs, and first-hand accounts of their use through co-design workshops. Below, we summarize our main findings, compile guidelines for applying badges, and discuss future work towards a more comprehensive framework for visualization badges.

7.1 Contribution Summary

As part of our framework, we define the concept of visualization badges, provide 132 examples of badges in a comprehensive catalog, and describe their attributes such as intent (*warning, confirmation, information*), scope (*data, analysis, visual representation, interaction, context*), genres (mono, ordinal, categorical, list, quantitative, score), and 23 badge topics (Sec. 4). We propose a first design for badges, including several options to integrate them with visualizations, satisfying three design criteria (Sec. 5). We also employed a rigorous methodology with complementary badge-collection mechanisms and five interdisciplinary co-design workshops with domain experts to evaluate our framework by creating, applying, discussing, and refining badges.

Like an iceberg, a visualization shows only the tip of deeper processes and decisions; visualization badges provide a lightweight way to surface these hidden layers for the reader. From the co-design workshops, we learned that visualization badges were viewed as a highly desired and potentially effective medium for communicating information about visualization design and data processing. **Badges can be seen as units of information** that provide structure for discussing which details are relevant to a project and which concepts an audience is or is not familiar with. This structure includes badge topics, intents, and scopes, with badge genres providing a more formal framework to think about badges and the information they convey. We found that the framework helps visualization authors reflect on their data processing, open-data practices, and their intended audience: *what do readers know about the data? what are their levels of general data and visualization literacy? what information is most important for correct interpretation?*

The discussions eventually showed that **applying badges is challenging and full of trade-offs**. One trade-off is between transparency on one side and effective communication on the other: transparency might suggest many badges on individual matters, while effective communication favors fewer badges that are most relevant to a specific audience. This tension also relates to the challenge of scalability (Sec. 5.1) and emphasizes that authors should carefully select badges and consider prioritizing them. This principle can be supported through our proposed aggregation designs (Fig. 4) and the application guidelines we outline below (Sec. 7.2). This finding confirms existing studies that warn of too much information overwhelming a reader [51]. Another trade-off is between displaying high-priority badges more saliently inside or beside a visualization, while keeping lower-priority badges "at a reader's disposal" elsewhere (or in aggregated form). While the complexity of negotiating and assigning badges was somewhat surprising, it is largely a consequence of the complex and often subjective nature of data analysis and visualization design. These processes rely on the honesty and willingness of the author to be transparent; we see a counterbalance to potential misuse in public scrutiny platforms (Sec. 7.3).

7.2 Applying Badges: Steps and Guidelines

We compiled the following phases (1–9) to support creating reusable badge schemas and applying badges to visualizations. Many of these steps can involve multiple people and entire teams with different expertise and authority over the visualization and badges. Authors who start from an existing badge schema can jump to Step 4, whereas those defining or updating a schema begin at 1.

1. **Analysis and visualization design**—Before applying any badges, consider all the visualization design and data processing decisions involved. The badge catalog can serve as a checklist, and while creating badges introduces an overhead, it provides you with an artifact that can be used to justify deliberate choices (e.g. an intentionally truncated axis). If a design decision cannot be adequately defended (e.g., through the description of a badge), then design revision should be considered. Note down each decision.
2. **Collect badge labels**—Then, repeat this process for all visualizations in a project to create a project-specific list of badges. The catalog can help inspire badge labels. For each badge, write a clear description that explains what it covers.
3. **Create badges and badge genres**—The next step is to resolve any ambiguities from this list and define clear badge labels and genres. For example, exclusive badges or badges with nuances can become Ordinal badges; badge labels pointing to multiple options can become Categorical or List badges; Score badges require a predefined scoring system and are the most challenging to create requiring a proper framework for criteria, which can be derived from individual badges. In this step, it can help to refine the badge descriptions to express more clearly the final badge label. Badge labels should be as short as possible (ideally 2-3 words) and use terminology known by the audience or standard in a given field.

4. **Assign intents, scopes, and topics** to clarify how each badge is used. If you cannot clearly assign an intent for all uses, consider either listing multiple intents or duplicating the badge.
5. **Store badges**—Badges, alongside their attributes and descriptions should be stored in a central repository, such as a code book, accessible to anyone potentially applying them to their visualizations. In more technical settings badges could be pulled out of a data base and rendered alongside a visualization.
6. **Assign badges to visualizations**—Generally, the number of badges per visualization should be kept low. Ideally, a visualization team creates prioritization guidelines to help decide which badges to show in which situations. Prioritization can happen on a global level (e.g., prioritizing data quality badges) or individually for each visualization, depending on the context. Priority levels can be binary *high/low* or systems with more steps if required. Eventually, each visualization points to a list of badges with their respective priorities. Ideally, each vis badge should convey one piece of information that distinguishes the chart from others.
7. **Design badge system**—If not using our standard design, choose a color scheme, backdrop style, and pictograms, if desired. Otherwise, match design decisions like mode, placement, visual design—with badge priorities.
8. **Place badges**—Badges with high priority should be rendered in salient designs (colored, LABEL, FULL), lower priority badges can be aggregated. We suggest grouping badges according to their scope or topic. Badges relevant to the entire project can be placed at the top or bottom of a page.
9. **Refine**—Once badges are published alongside a visualization, try to obtain feedback from actual readers; either in a dedicated study or by observing real users. Assigning badges is an act of declaring and disclosing hidden information, which does not free the authors of liability or criticism. Refine badge labels and descriptions as well as design decisions to minimize misinterpretation.

The entire process can resemble a double-diamond structure with cycles of exploration (badge collection, badge assignment) and evaluation (badge creation, badge refinement). In cases of larger visualization projects, the process will involve team members with different expertise in data, analysis, visualization, and the respective domain.

7.3 Further Badges Usage Scenarios

Besides supporting visualization authors in disclosing information, we identified further usage scenarios for visualization badges.

Badges could help **education in data and visualization literacy** [2]. For example, the badge catalog captures this breadth in a very concise way, allowing the catalog to be an educational framework for students, educators, and practitioners. By consulting the badge taxonomy and thinking about which vis badges might apply in particular contexts, students can develop more advanced visualization literacy and strengthen their design skills. For example, the catalog could serve as a checklist for identifying potentially misleading issues in visualizations, asking students to assign badges to visualizations. Likewise, a visualization design class can include exercises on creating badges to have students reflect on their design decisions and how to expose them, similar to approaches to literate visualization [95].

Badges could also guide visualization design through **informing quality assurance through automation**. With the rise of generative AI and automated analysis tools, future applications may automatically assign badges based on data or visualization properties, like linting [19, 42, 63]. However, such automation may lack the contextual nuances of deliberate authors' decisions to disclose information. [95]. However, badges can become a tool for **public scrutiny of visualizations and data**. For example, collaborative platforms or forums (e.g., [87]) can allow community members to tag visualizations with relevant vis badges or suggest new ones. Beyond scrutiny, such platforms could become tools to establish and refine best data practices. An open tagging approach could also include tracking badge assignments across sites and projects, ultimately leading creators to a deeper understanding of user needs and preferences. Eventually, such 'badge tagging platforms' could provide valuable data to study how visualizations are understood by a large, diverse, and public audience [49].

7.4 Studying Badges Effectiveness for Interpreting Visualizations

The critical next step in better understanding visualization badges is to understand the real impact badges have on reading visualizations: *Do readers understand the labels? Do they take badge information into account? Do badges increase trust?* The visualization badge framework developed in this paper and evaluated with visualization authors can help inform the possibly comprehensive setups of such studies. For example, controlled user studies could test a set of visualizations with and without visualization badges (and possibly a version with only textual information). Such studies will require careful balancing of the badges assigned, the visualizations chosen, and the choice of participants; crowd-sourced studies could yield good results here. Qualitative studies can complement such quantitative studies, but require actual projects, such as our collaborative projects, to include the badges; again, such projects require lots of internal discussion to create the 'right' badges for their specific demands.

The biggest challenges in these studies will be how to *assess* the impact of visualization badges, a problem already described in the literature [13, 14, 31, 62]; *what are good measures to assess if someone takes them into account? How can we assess the difference in reading a visualization with or without a badge?* One particular problem with such studies is that people have varying prior knowledge about visualization and also learn during the study, which can bias the results. Large sample sizes, e.g., through crowd-sourcing, could be an option but might make it harder to measure success. Most likely, badges require studies in-the-wild, integrated into real visualization projects seen by real readers, which naturally comes with its own challenges.

7.5 Towards a Comprehensive Framework for Visualization Badges

With these contributions and reflections in mind, we can envision a more comprehensive framework for visualization badges and the communication of provenance information. Such a framework could not only provide empirical evidence and guidelines about how people understand visualization badges, but could also provide more technical solutions for their creation, deliberation, application, and tracking.

For example, **badge editors** can help visualization authors and authoring teams create and design badges, using a predefined set of templates and design options. Badges could then be **centrally stored**, deliberated, and versioned. A visualization project could publish their **bespoke badge list** regularly for wider public reuse. Other visualization authors in the same domain, e.g., peace research, social sciences, earth sciences, could then view and **re-use badges** for their own visualizations, citing an already deliberated and agreed-on badge list.

These projects could also collaborate with and contribute to the original badge list creators aiming to achieve **field-wide standards** for badges that cover common practices in this field. Alternatively, they could update and release their own badge list, covering a complementary or subset of badges, e.g., for a subfield or specific practice. Over time, standardized and reusable badge lists could emerge, subject to intense scrutiny and debate.

As already indicated in Sec. 7.4, badges used in real-world projects would open up opportunities for **studying the application and use of badges**, including the proliferation of certain badge lists and their deliberation. Tools could also help with the **analysis and tracking** of badge applications as well as assisting authors in searching for, and assigning, relevant badges to their projects.

In summary, we see visualization badges as a novel, tangible, highly applicable, and easy-to-create means of communicating provenance and design information alongside a visualization. Our framework is meant to complement efforts toward achieving trust [62], onboarding in visualization [81], education in visualization [2], and broader data literacy. Yet the success of visualization badges depends on establishing common guidelines, selecting only the most relevant badges, and avoiding badge anxiety that distracts or overwhelms users.

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APPENDIX OF

Visualization Badges: Communicating Design and Provenance through Graphical Labels Alongside Visualizations

Valentin Edelsbrunner[1], Jinrui Wang[2], Alexis Pister[2], Tomas Vancisin[2], Sian Phillips[2], Min Chen[3], Benjamin Bach[1,2]

[1]Inria Bordeaux, France
[2]University of Edinburgh, UK
and [3]University of Oxford, UK

A Badge creation and analysis

To explore the idea of visualization badges, we first needed a comprehensive list of badges and possible attributes or a taxonomy of these badges. To that end, we collected information considered relevant to be shown alongside visualizations for which we employed three complementary approaches (Fig. 8): (a) a review of scientific papers presenting frameworks, studies and guidelines on design flaws, data provenance, metadata, trust, and visualization design communication (b) manually coding 80 real-world visualizations from well-known news magazines; and (c) co-creating badges through three workshops with domain experts for their respective visualization projects. Each of these methods yielded a set of badges that were eventually consolidated, refined, and analyzed into a comprehensive list of 132 badges. In this section, we detail each of the above-mentioned steps. The final catalog of badges is found on our supplementary website https://vis-badges.github.io.

A.1 Badge collection

(1) Literature Survey. Visualization badges can surface information from every step of the visualization creation process, including data collection, processing, design, interpretation and exploration. Consequently, relevant contributions appear in diverse fields such as data visualization, human-computer interaction, and data science. To capture this breadth, we looked at proceedings and collections of major venues:

- ACM CHI,
- Communications of the ACM,
- EuroVis, and
- IEEE VIS,
- PacificVis,
- TVCG

reading titles, abstracts, and (where necessary) full texts, mainly searching for frameworks, surveys or guidelines that inform potential badges. This initial pass yielded 20 papers. Additional keyword searches derived from the initial collection and colleague recommendations increased our total set to 33 papers. Every paper falls in one of these categories:

- Data Provenance, information on how data was collected, processed, or modeled (e.g., [39, 72]).
- Design Flaws, that undermine effective presentation (e.g., [54, 59]).
- Frameworks and Guidelines including methods and best practices for creating, communicating, or exploring visualizations (e.g., [48, 64]).
- Metadata, Contextualization, and Trust information not directly present in the visualization (e.g., [13, 14, 31]).

We read each collected paper and used them as a foundation to identify specific informational elements that could become visualization badges, noting any statement containing or soliciting details potentially relevant to visualization readers. Examples of such statements included information that analysts should disclose with a dataset to increase transparency and reproducibility (e.g., "Over what timeframe was the data collected?" or "Has the dataset been used for any tasks already?" [39]). Other examples involved structured lists, for example 28 pieces of metadata and contextual information, such as "Description of a potential misunderstanding of the chart" or "Names of the people who created the chart" [13, 14]. Again other papers provide curated catalogs of real-world design flaws in visualizations (e.g., truncated axes, 3D effects, lack of labels) [54, 59]. We noticed that papers on the same topic tended to converge on similar recurring badge candidates. This step resulted in approximately 75 candidate badges.

Eventually, P1 and P2 held regular discussions over a period of three months, examining each statement and formulating possible badges. At this point we decided that a visualization badge should have a **label**, ideally 1-3 words, conveying an important statement that will help to read and interpret the visualization, if shown alongside it. Examples include Contains Overlapping Elements, Adapted Elsewhere or Truncated Axis. A **description** of 1-2 sentences explaining the information behind the badge (e.g., *Visual elements may overlap in dense areas*) and possible **free-form tags** that we would use later to form a proper taxonomy, like *Analysis*, *Interpretation*, and *Data*.

We decided to exclude badges about purely deceptive design flaws which would not be attributed by the author of a visualization themselves. For example badges warning a reader about "illegible text" or "legend missing", would not be directly relevant to authors disclosing information to improve interpretation of their visualization; in our list, these badges almost exclusively originated from the context of linting and design feedback (e.g., [54, 63]). After these steps, we ended up with approximately 65 badges.

(2) Visualization coding. Complementing this first list of 65 badges, we extended our badge creation and collection to real-world examples of visualizations from news articles. We used a collection of 80 data articles, used by Hao et al. to code data article design patterns [44]. The collection included articles from The Financial Times (20), The New York Times (18), The Economist (16), The Guardian (14), The Times (8), and BBC News (4). The total corpus contained about 3-5 individual visualizations per article (313 in total) and is provided as supplementary material. Five authors P1-P5 (two PhD students, two postdocs, and one senior researcher) independently reviewed all visualizations in sets of 16 non-overlapping articles. For each visualization, they noted (a) textual information disclosed alongside the visualization, such as footnotes or methodology explanations (e.g., an article in *The New York Times* article #17, P1 stated at the end of the article that multiple data sources were used, resulting in a Multiple Data Sources badge), and (b) information about the visualization design or data that the coder would consider relevant to disclose if they were the author (e.g., Interactive Pre-Filter *The Economist*, #10, P2 described as *"This interface is interactive. Some data is initially filtered out, but users can change that."*

Alongside identifying information such as article ID, visualization ID, coder ID, for each badge candidate, a coder attributed the same scheme described in (1) Literature Survey: label, description and free-form tags. In addition, two new coding dimensions were introduced, *intent*, capturing whether a badge was rather positive, negative, or neutral and based on the free-form tags, an exclusive badge *scope* was derived. Both dimensions are discussed in detail in Sec. 4.1 and Sec. 4.3 respectively.

Eventually, all coders discussed their collected badge candidates. Disagreements were discussed, and badges lacking consensus were dropped (e.g. "unclear text annotation") or refined (e.g, "Handwritten data source" to Raw Data Available. This step yielded 42 badges. **(3) Co-design workshops.** Following the literature survey and visualization coding, we held 3 workshops to co-design badges with domain experts for their visualizations (see Tab. 1 for participant information). The goal was to create badges with visualization authors in real-world contexts and to surface any badges not captured by coding existing examples and literature. Incorporating these badges into participants' visualizations helped reveal to diverse audiences the breadth of qualitative data collection, manual processing, and other curation steps involved in visualization design. Each workshop focused on a different ongoing collaboration and individual visualization project. These projects were

- **Peace visualizations**: This project is the result of a year-long interdisciplinary collaboration between visualization researchers and researchers in peace and conflict resolution. The collaboration yielded multiple visualizations, including dashboards, storytelling, and interactive exploratory visualizations meant to support professional peace and conflict researchers with relevant data about these processes as well as to inform a wider public. In the workshop, six participants (P3, P5, and P11 - P14) with expertise in peace and conflict resolution, digital humanities, data science, and information visualization. P3 and P5 are authors on this paper, but they are also directly involved in the visualization design and creation for this project.
- **Co-Benefits atlas**: a new collaboration to create a visualization atlas [91] on the topic of co-benefits in CO_2 emission reductions with researchers in climate change and adaptation. The data is mainly modeled and the planned atlas is meant to communicate the resulting data to policy makers while making the data fully available and explorable. The atlas will contain many visualization types ranging from classic charts to interactive maps, dashboards, reports, and policy briefs. The workshop included 3 experts (P6-P8) with a background in climate data modeling and analysis, climate change consultancy and communication and P4, P6 with an expertise information visualization. P3(not present during workshop) P4 and P6 are authors of this paper and are responsible for building and designing the atlas.

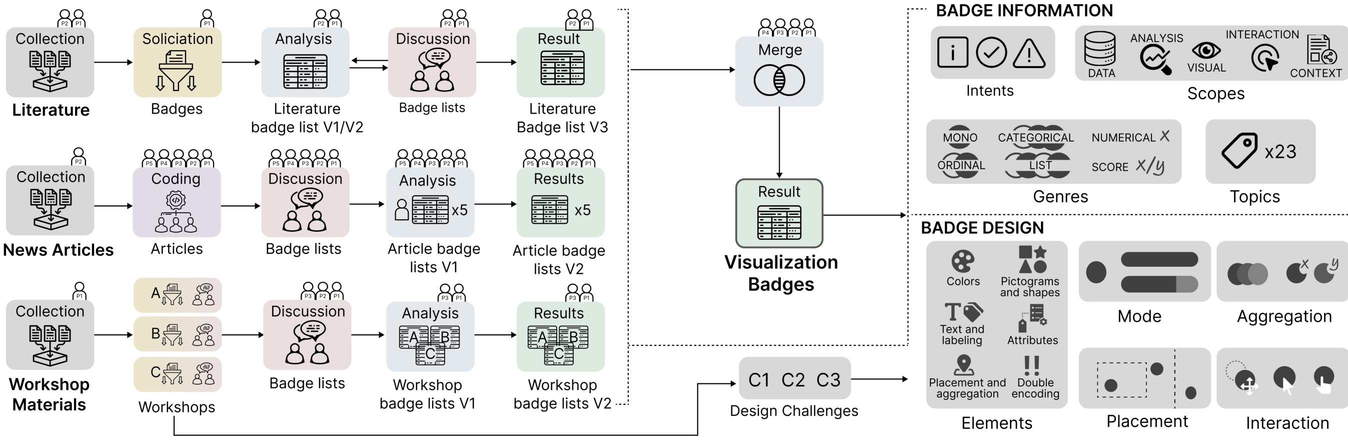

Fig. 8: Methodology overview of (a) badge collection through literature search, coding real-world news articles and co-design workshops, which resulted in (b) a visualization badges catalog, (c) badge information categories and a badge design space.

- **Earth dashboards**: the NASA Earth Now Dashboard [53] is an initiative by NASA to display live NASA earth data about the planet to wider public. Data about temperature, aerosols, or precipitation are obtained from NASA satellites, then processed (e.g., to identify wild-fires) and eventually shown in various animated visualizations using scientific visualization techniques and high-resolution geographic maps. Given the complexity, global scope, and high granularity of the data, visualizations in this project do make heavy use of simplification, both in terms of analysis and visualization (e.g., smoothing and interpolations). This workshop included 6 members of NASA's Earth Now team (P15-P20) with expertise in earth and data science, geographic information systems and information visualization.

Each workshop lasted two hours and asked participants to create badge names and badge descriptions for one or more visualizations they were designing (or involved in the design process). We asked participants to think about badges they would assign as a *visualization author* (i.e., conveying information you want your audience to keep in mind while reading and interpreting the visualization). Eventually, each participant shared their badges and we discussed them among the entire workshop team (e.g., removing duplicates, shortening and clarifying names, asking for clarifications on the description, etc.). The workshops resulted in a total of 48 badges.

A.2 Badge consolidation

Finally, P1-P4 consolidated the collected badges from the literature survey(64), from the news article coding(42), and the workshops(48) into one list. This process involved

- *resolving similar badges* by merging duplicate or closely related entries, refining or disambiguating names and descriptions where necessary. *applying attributes consistently*, ensuring that each badge has a concise label, description, intent, scope a topic. We also discussed precise terminology for the respective attributes detailed in Sec. 4.
- *Making badges atomic* by splitting up badges that actually covered several different concepts (e.g. "Intended Audience" was split into For Experts Only, For General Audience and For Policy Makers). Where these new, smaller badges formed coherent sets, we documented them as "categorical" or "list badges" (Sec. 4.2).

Through *refining free-form tags*, we integrated each badge's tags into our revised structure, ensuring consistent, accurate categorization across the entire set. The result is a comprehensive list of 132 badges (see appendix or badge catalog).

B Examples of Badge Usage in Real-world Context

This appendix elaborates on the justifications for selecting badges made during three co-design workshops with domain experts. The results are depicted in Fig. 6. High-resolution versions of each example can be found online at `https://vis-badges.github.io`.

ID	Role	Expertise	Years
P1*	Vis Designer	Data visualization	1
P2*	Researcher	Data visualization, HCI	12
P3*	Vis designer	Data visualization	4
P4*	Vis designer	Data visualization	3
P5*	Vis designer	Digital humanities	7
P6	Researcher, Outreach	Policy communication	15
P7	Research lead	Climate intervention modeling	10
P8	Domain researcher	Quantitative political science	9
P9	Software engineer	Web development	12
P10	Domain researcher	Peace and conflict database	15
P11	Data engineer	Data engineering	6
P12	Software/vis engineer	Data services, earth science	30+
P13	Software/vis engineer	Fires, Biogeography	3
P14	Vis designer	Data visualization	20
P15	Application developer	Software development	25
P16	Research, outreach	Satellite earth observation	15
P17	Project lead	Earth/satellite visualization	18
P18	Modeller, Analyst	Socio-econ. analysis	4
P19	Programme Director	Climate actions consultancy	15
P20	Vis designer	Data Visualization	1

Table 1: People involved in all workshops, with their role and expertise in the respective collaborative projects; "years" refer to years of experience after PhD. P1-P5(*) are co-authors of the paper, where P1-P2 were workshop organizers and coders, P3-P5 joined as participants because they are actively involved in the ongoing visualization project collaborations.

B.1 Peace Visualization: Messy Timeline - Back and Forth in Peace Negotiations

The Messy timeline was designed to illustrate how peace processes were shaped and progressed as peace agreements were signed in different stages. The visualization intends to break assumptions that "peace negotiations progress from one stage to the next" while the messy reality is they go back and forth or even face abrupt intervals. During workshops, the following popular badges were selected by participants with rationales provided, some in participants quotes.

- Technical Terminology *"Users may not be aware of the definitions of the terminology used, or why the order of these stages matter in this visualization."*[P13]
- Overlapping Elements On one hand, this badge *"let the audience know this is an intentional design decision, to show how messy peace processes are"*[P3] while on the other hand we place all recorded peace processes in the database the overlaps are inevitable.
- Mind False Conclusions *"As intention with visualization is to break assumptions of how the trajectory of processes are in reality, we do not want users to look at a process they think is 'successful', and draw conclusions that this trajectory results in a successful process."*[P14]

- Can Sort & Filter The filtering feature provided by a drop-down list is placed on top-right corner of the screen which may not be obvious for new users.
- Open Data The underlying data is both openly accessible and provided by the same peace and conflict research group.

B.2 Co-Benefit Atlas: Local Area Report

In this visualization atlas collaboration where we communicate a series of co-benefits data gained from reducing CO2 emissions and reaching net zero goals by 2050. A local area report contains comprehensive charts on regional information ranging from co-benefit values in different transitioning pathways, distribution of co-benefits across smaller data zones, and impacts on different types of households. These are some of the badges discussed during the workshops that apply to entire page and should be aggregated:

- Contains Modeled Data The co-benefit values are predictions output created by a supercomputer model from 2025 to 2050. There cannot be exact promised benefits.
- Aggregated Data Co-benefit values are calculated on granular small data zones and then aggregated for the entire local area.
- Open Data The research outputs will be openly accessible to public audiences.

There are two more badges, that will be placed beside specific visualizations, namely a Major Finding for any chart that disclose key information directing to detailed explanation, and a Qualitative Categories badge for those metrics describing household characteristics using ordinal numbers as categories instead of implying any linear scales.

B.3 Greenhouse Gases Hyperwall Dashboard

The NASA hyperwall dashboards are high resolution dashboard videos that are dedicated to large exhibitions. Audience will stand in front of the wall to read the visualizations, which leads to the selected badges placed inside the visualization next to the dashboard-title. We adopted the dark mode badge styles to match the tone of the dashboards. The example dashboard depicts the modeled flow of greenhouse gases from space, air, and ground. Participants selected the following examples:

- Contains Modeled Data These visualizations use modeled data (e.g., GEOS).
- For General Audience They are frequently used in exhibitions, scientific storytelling, and educational settings.
- Multiple Data Sources Data comes from NASA and its partner agencies.
- Adapted Elsewhere The hyperwall is listed in a digital library and is free for affiliated members to adapt and tell their own stories.
- Data Creator(s) Attributed The original data contributors are credited.

C Badge Catalog

Here we present our complete catalog of 132 visualization badges collected through our literature review, real-world magazine coding, and five co-design workshops (Appendix A). For more information about the table structure we point to Section 4. The same catalog is also available at `https://vis-badges.github.io`.

The catalog begins on the next page.

Table 2: Visualization Badge Catalog.

LABEL	DESCRIPTION	INTENT	SCOPE	TOPIC
Data Citation	References a published work that describes or validates the dataset.	Confirmation	Context	Attribution
Trusted Data Source	Indicates that the data is from a source the author deems reliable or reputable.	Confirmation	Context	Source
Data Creator(s) Attributed	Identifies the individual or team responsible for collecting the dataset.	Confirmation	Context	Attribution
Adapted Elsewhere	Indicates that the same data or visualization was reused by third parties. This can be a sign of endorsement and validity of the data or visualization.	Confirmation	Context	Usage
Major Finding	Indicates that the visualization presents a key or central result.	Confirmation	Context	Interpretation, Usage
Attributed Visualization Creators	Indicates that the individual or organization responsible for creation is acknowledged.	Confirmation	Context	Attribution
Terminology Explained	Indicates that definitions or clarifications of specialized terms are provided.	Confirmation	Context	Audience
Background Reading Available	Indicates that extra materials or readings are provided for additional context.	Confirmation	Context	Usage
Experts Involved	Indicates that domain experts provided insights or guided the design and analysis	Confirmation	Context	Attribution
No AI Involved	Confirms that no AI was involved in creating this visualization.	Confirmation	Context	Attribution, Bias
User-Tested Vis	Indicates that the visualization was validated through user testing (e.g., user study).	Confirmation	Context	Audience
Time Range Selected	Indicates that data is shown only for a chosen timeframe, excluding earlier or later periods.	Information	Context	Filtering, Exploration, Time
Data Filtered	Indicates that data was included or excluded based on specific conditions or statuses.	Information	Context	Filtering, Exploration
Geographically Filtered	Indicates that the dataset is filtered by geographic criteria.	Information	Context	Filtering, Exploration
Demographic Filter	Indicates that data was filtered by demographic attributes (e.g., age, gender).	Information	Context	Exploration, Filtering
For General Audience	Indicates that this visualization was designed to be easily understood by a general audience without domain-expertise, i.e., that it might make some simplifications or omits some complexity	Information	Context	Audience
For Experts Only	Indicates that the chart requires specialized or technical domain knowledge.	Information	Context	Audience
For Policy Makers	Indicates that the chart is primarily aimed at government officials or decision-makers, the visualization contains very condensed, high-level information.	Information	Context	Audience
Public Domain Visualization	Indicates that the chart is free of copyright restrictions.	Information	Context	License
Vis License: CC0	Specify the license for chart distribution as CC0 public domain.	Information	Context	License
Public Domain Data	Indicates that the dataset is free from copyright or usage restrictions.	Information	Context	License
Data: CC0 Dedication	Indicates that the data is under the Creative Commons Public Domain Dedication (CC0).	Information	Context	License
Data: ODC-PDDL	Indicates that the dataset is licensed under the Open Data Commons Public Domain Dedication and License (PDDL).	Information	Context	License
Complex Units	Indicates that this visualization contains units likely unfamiliar to the intended audience requiring explanation or reference points	Warning	Context	Audience, Interpretation
Sensitive Topic	Indicates that the chart covers a sensitive topic that may upset some viewers.	Warning	Context	Audience
Technical Terminology	Indicates that the visualization uses domain-specific terms that may be unfamiliar to many.	Warning	Context	Audience
AI-Generated Visualization	Indicates that the chart was produced by generative AI tools(e.g.,GPT,DALL-E).	Warning	Context	AI

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Table 2: Visualization Badge Catalog cont..

LABEL	DESCRIPTION	INTENT	SCOPE	TOPIC
AI-Generated Captions	Indicates that descriptive text or annotations were produced by an AI system.	Warning	Context	AI, Interpretation
Can Sort & Filter	Indicates that viewers can reorder or filter data for a custom view.	Confirmation	Interaction	Tools, Exploration
Details-on-Demand	Indicates that details appear when elements are hovered or selected.	Confirmation	Interaction	Exploration
Device-Responsive	Indicates that the chart adapts to different screen sizes and aspect ratios.	Confirmation	Interaction	Exploration, Accessibility
Can Mouse Over	Indicates that hovering over elements reveals additional details.	Information	Interaction	Exploration
Zoomable	Indicates that the map can be zoomed in or out.	Information	Interaction	Exploration
Can Sort	Indicates that users can reorder elements by a certain dimension.	Information	Interaction	Exploration
Parameterizable	Indicates that users can modify parameters or settings.	Information	Interaction	Exploration
Brushing & Linking	Indicates that users can brush or highlight elements within or across multiple visualizations.	Information	Interaction	Exploration
Interaction Linked Across Multiple Views	Indicates that interactive changes in one view affect other views (e.g., linked small multiples).	Information	Interaction	
Interactive Pre-Filter	Indicates that the data is initially pre-filtered but can be manually adjusted.	Warning	Interaction	Exploration, Filtering
Alternative Units as Reference	Provides a secondary unit or scale to clarify the primary measurements (e.g., kilometers vs. miles).	Confirmation	Visual Encoding	Interpretation
Points Match Exact Locations	Indicated that symbol positions have exact coordinates for the event.	Confirmation	Visual Encoding	Maps
Uncertainty Visualized	Indicates that statistical or model uncertainty (e.g., error bars, confidence bands) is shown.	Confirmation	Visual Encoding	Uncertainty
Colorblind Safe	Indicates that color choices remain distinguishable for colorblind viewers.	Confirmation	Visual Encoding	Accessibility, Color
Printer Safe	Indicates that the design remains clear and readable when printed	Confirmation	Visual Encoding	Accessibility
Area Encoding	Indicates that the size of visual elements is calculated as function of their value mapped to the area.	Information	Visual Encoding	
Approximate Times	Indicates that the displayed timeframe is approximate.	Information	Visual Encoding	Time
Standard Scale Used	Indicates that the visualization uses a standard scale (e.g., linear).	Information	Visual Encoding	Interpretation
Non-Area-Preserving Projection	Indicates that the chosen map projection does not preserve consistent area proportions.	Warning	Visual Encoding	Maps
Points Don't Match Exact Locations	Indicates that symbol positions on the map may not reflect precise coordinates	Warning	Visual Encoding	Maps, Uncertainty
Uncertainty Omitted	Indicates that known uncertainty is not shown in the visualization.	Warning	Visual Encoding	Uncertainty
Dual-Axis Encoding	Indicates that two different (vertical) axes are used to represent separate variables in the same chart.	Warning	Visual Encoding	Axes, Interpretation
Truncated Axis	Indicates that an axis starts from a non-zero point, explaining the rationale for that	Warning	Visual Encoding	Axes, Interpretation
Inconsistent Axis Intervals	Indicates that intervals on the axis are not uniform, potentially confusing scale perception.	Warning	Visual Encoding	Axes
Inverted Axis	Indicates that an axis direction is reversed with respect to an otherwise intuitive direction, e.g., higher values on the top, time passing from left to right, etc.	Warning	Visual Encoding	Axes, Interpretation
Differing Y-Axis	Indicates that multiple charts use different y-axis scales or baselines.	Warning	Visual Encoding	Axes, Interpretation
Log Scale	Indicates that the data is plotted on a logarithmic scale.	Warning	Visual Encoding	Axes

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Table 2: Visualization Badge Catalog cont..

LABEL	DESCRIPTION	INTENT	SCOPE	TOPIC
Size Distortion	Indicates that element sizes may not strictly match their underlying data values.	Warning	Visual Encoding	
Small Values Exaggerated	Indicates that very small data points are magnified for better visibility.	Warning	Visual Encoding	
Invisible Small Values	Indicates that extremely small items may not be visible at the current scale, e.g., they cannot be seen at the current screen resolution or zoom level.	Warning	Visual Encoding	
Overlapping Elements	Indicates that elements can overlap in dense areas.	Warning	Visual Encoding	
False Friend	Indicates that a visualization may resemble a common visualization yet might require different interpretation	Warning	Visual Encoding	Interpretation, Bias
Varying Scales	Indicates that multiple adjacent charts use different axis scales, complicating comparison across charts.	Warning	Visual Encoding	Axes
Rainbow Required	Indicates that a rainbow-like color gradient is required to show the specific data.	Warning	Visual Encoding	Color
Redundant Encodings	Indicates that more than one visual channel (e.g., color and shape) encodes the same attribute.	Warning	Visual Encoding	Interpretation
Labels Omitted	Indicates that axis text is provided in accompanying descriptions rather than on the axis itself	Warning	Visual Encoding	Axes
Estimated Geographic Boundaries	Indicates that shapes or borders are inferred rather than exact.	Warning	Visual Encoding	Maps
Uneven Time Intervals	Indicates that the intervals between time points are inconsistent.	Warning	Visual Encoding	Time
Data Off the Map	Indicates that some data points lie outside the current view and are not displayed.	Warning	Visual Encoding	Maps
Irregular Patterns	Indicates that there are irregular patterns that may not yield meaningful conclusions.	Warning	Visual Encoding	Uncertainty
Interval Breaks	Indicates that an axis in the visualization has one or more breaks, i.e., unequal intervals.	Warning	Visual Encoding	Interpretation
Positionless Elements Not Shown	Indicates that this visualization does not or cannot show elements without a geographic position.	Warning	Visual Encoding	Maps
Simplified Geographic Boundaries	Indicates that geographic boundaries have been simplified to improve readability of this visualization.	Warning	Visual Encoding	Maps
Analysis Tools Attributed	Indicates that data analysis was done using a stated, available tool.	Confirmation	Analysis	Tools
Human-Verified AI	Indicates that humans verified AI-generated results.	Confirmation	Analysis	Attribution, Bias
Missing Values Handled	Indicates that missing data had been treated by some method, e.g., by imputation, deletion, or any other custom method.	Information	Analysis	Constraints, Uncertainty, Preprocessing
Outliers Removed	Indicates that extreme values were excluded or adjusted, possibly affecting distributions or variance.	Information	Analysis	Preprocessing, Bias, Transformation
Binning Applied	Indicates that continuous values were grouped into categories.	Information	Analysis	Preprocessing, Transformation
Data Normalized	Indicates that values were scaled or standardized (e.g., min–max, z-score) for alignment.	Information	Analysis	Preprocessing, Transformation
Tokenization Applied	Indicates that text was split into discrete tokens (words or subwords) for analysis.	Information	Analysis	Preprocessing, NLP
Part-of-Speech Tagging Applied	Indicates that each token was labeled with a grammatical function (e.g., noun, verb).	Information	Analysis	Preprocessing, NLP
Features Extracted	Indicates that additional features (e.g., word embeddings) were created from raw data.	Information	Analysis	Preprocessing
Stemming Applied	Indicates that words were reduced to their base forms, removing morphological variations.	Information	Analysis	Preprocessing, NLP

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Table 2: Visualization Badge Catalog cont..

LABEL	DESCRIPTION	INTENT	SCOPE	TOPIC
Stopwords Removed	Indicates that common filler words were removed to emphasize key terms.	Information	Analysis	Preprocessing, NLP
Random Sampling	Indicates that data points were selected using a purely random or probabilistic method.	Information	Analysis	Sampling
Stratified Sampling	Indicates that subgroups (strata) were identified and then sampled proportionally.	Information	Analysis	Sampling
Systematic Sampling	Indicates that data points were chosen at regular intervals.	Information	Analysis	Sampling
Cluster Sampling	Indicates that entire clusters were used as sampling units.	Information	Analysis	Sampling
95% CI Error Bars	Indicates that 95% confidence intervals are displayed; out-of-range values are still possible but less likely.	Information	Analysis	Uncertainty
Aggregated Data	Indicates that values were combined or averaged, which may hide variation.	Information	Analysis	Aggregation
Adjusted Baseline	Indicates that a non-zero or shifted reference point is used (e.g., per capita, moving average).	Information	Analysis	Transformation
Shows Top N	Indicates that only the top N elements are displayed, based on a certain criterion.	Information	Analysis	Filtering
Composite Index	Indicates that a combined metric synthesized from multiple factors is displayed	Information	Analysis	Aggregation
Qualitative Categories	Indicates that data is grouped into descriptive categories (e.g., high, medium, low).	Information	Analysis	Transformation
Semi-Auto Data Processing	Indicates that data processing involves both machine automation and manual cleaning.	Information	Analysis	Tools
Additional Manual Cleaning	Indicates that the data processing was cross-checked manually.	Information	Analysis	Tools
Analysis Constraints	Indicates that the data analysis process has known limitations.	Warning	Analysis	Constraints
May Contain Bias	Indicates potential systematic distortion from collection, sampling, or modeling processes.	Warning	Analysis	Bias, Uncertainty
May Contain Noise	Indicates that random variation or measurement errors may be present.	Warning	Analysis	Uncertainty
Automatically Labeled Data	Indicates that some or all labels in the dataset were generated automatically.	Warning	Analysis	NLP, Uncertainty
Actual Time Offset	Indicates that the chart's latest timestamp lags behind real time.	Warning	Analysis	Uncertainty, Time
Data Manually Removed	Indicates that some data points were intentionally removed for specific reasons.	Warning	Analysis	Constraints, Exploration
Simpson's Paradox	Indicates that aggregated data can mask or reverse trends visible in subgroups (Simpson's paradox).	Warning	Analysis	Interpretation
Correlation $\neq$ Causation	Reminds viewers that observed correlation may not imply causation.	Warning	Analysis	Interpretation
Possible Visual Artifacts	Indicates that the visualization algorithm or scaling method may produce patterns not present in the underlying data	Warning	Analysis	Interpretation
Rounding Errors	Indicates that data in the visualization may contain rounding errors, e.g., values not adding up to 100%.	Warning	Analysis	Constraints
Mind False Conclusions	Warns the reader that a seemingly obvious visual pattern may lead to false conclusions	Warning	Analysis	Interpretation
Null Values Removed	Indicates that null or infinite values have been excluded from the data.	Warning	Analysis	Constraints
AI-Assisted Analysis	Indicates that AI methods (e.g., clustering, pattern recognition) were used in data analysis.	Warning	Analysis	AI
AI-Derived Insight	Indicates that the key insights rely on AI-based evaluation.	Warning	Analysis	AI
Possible AI Bias	Indicates that the visualization may reflect distortions introduced by AI systems	Warning	Analysis	Bias, AI
Data Sources Disclosed	Indicates that the data sources for this visualization are known and listed.	Confirmation	Data	Source

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Table 2: Visualization Badge Catalog cont..

LABEL	DESCRIPTION	INTENT	SCOPE	TOPIC
Open Data	Indicates that the visualization uses publicly accessible data, which can be downloaded, verified, or reused.	Confirmation	Data	Availability
Dataset Linked	Indicates that a link to the dataset is provided with the visualization.	Confirmation	Data	Availability
Raw Data Available	Indicates that unprocessed material (e.g., images, scans, text) is accessible.	Confirmation	Data	Source, Availability
Data Up-to-Date	Indicates that the dataset reflects the latest available data.	Confirmation	Data	Availability, Time
Collection Period Specified	Indicates that the timeframe of data collection is specified.	Confirmation	Data	Source
Dynamic Data	Indicates that the information is refreshed regularly or continuously, so the chart may change over time.	Information	Data	Availability, Time
Heterogenous Data	Indicates that the visualization merges data from diverse sources, e.g., text, images, or sensors.	Information	Data	Source
Human Survey Data	Indicates that the data comes directly from individuals' statements or surveys.	Information	Data	Source
Derived Data	Indicates that the visualization shows data created by algorithms or processes.	Information	Data	Transformation
Manually Collected Data	Indicates that humans actively gathered or annotated the data (e.g., via observations or coding).	Information	Data	Source
Sensor Data	Indicates that data is captured by physical instruments (e.g., sensors, lab equipment).	Information	Data	Source
API-Based Collection	Indicates that data was retrieved via an API (e.g., social media or open-data endpoints).	Information	Data	Source
Multiple Data Sources	Indicates that datasets from multiple origins were combined, likely with some aggregation.	Information	Data	Source
Single Data Source	Indicates that the visualization relies on data from a single source.	Information	Data	Source
3D	Indicates that the chart visualizes three-dimensional or volume-based measurements. The chart may contain occlusion.	Information	Data	Source
Secondary Data	Indicates that the dataset is derived from secondary or aggregated sources rather than raw data.	Information	Data	Source
Data Quality Constraints	Indicates that the data has known limitations.	Warning	Data	Constraints
Missing Data	Indicates that parts of the data are missing.	Warning	Data	Constraints, Uncertainty
Contains Modeled Data	Indicates that some or all of the dataset is derived from algorithmic modeling.	Warning	Data	Uncertainty, Bias
Contains Predictions	Indicates that some or all of the data represents future predictions with inherent uncertainty.	Warning	Data	Uncertainty, Bias
Known Data Gap	Indicates that there is a known gap in the dataset.	Warning	Data	Uncertainty, Constraints
AI-Generated Data	Indicates that part or all of the dataset was generated by an AI model.	Warning	Data	AI, Uncertainty